FISEVIER

Contents lists available at ScienceDirect

Energy Economics

journal homepage: www.elsevier.com/locate/eneeco



Uncovering household indirect energy-saving responsibility from a sectoral perspective: An empirical analysis of Guangdong, China



Wei Zhen ^a, Quande Qin ^{a,b,c,*}, Zhangqi Zhong ^d, Li Li ^a, Yi-Ming Wei ^{c,e}

- ^a Department of Management Science, College of Management, Shenzhen University, Shenzhen 518060, China
- ^b Institute of Urban Governance, Shenzhen University, Shenzhen 518060, China
- ^c Center for Energy and Environmental Policy Research, Beijing Institute of Technology, Beijing 100081, China
- ^d School of Economics, Zhejiang University of Finance and Economics, Hangzhou 310018, China
- ^e Collaborative Innovation Center of Electric Vehicles in Beijing, 100081 Beijing, China

ARTICLE INFO

Article history: Received 28 November 2017 Received in revised form 23 April 2018 Accepted 1 May 2018 Available online 4 May 2018

Keywords:

Environmentally extended input-output analysis Household indirect energy consumption Energy-saving responsibility Structural path analysis Guangdong Province

ABSTRACT

Household indirect energy consumption (HIEC) is a major part of household energy consumption. It is critical to uncover energy-saving responsibilities associated with regional HIEC for China to respond climate change. In this study, we investigated the HIEC of Guangdong Province in 2012 from a sectoral perspective, using environmentally extended input-output analysis. Structural path analysis and sensitivity analysis were used to assess the key paths of the different production layers (PLS) for total, urban, and rural HIEC. Our results show that: (1) there are significant differences between urban and rural HIEC. (2) The "Electricity and Steam Production and Supply", "Transport, Storage, Postal and Telecommunication Services", and "Residential Services" sectors are the main drivers of both urban and rural HIEC. Furthermore, sectors with large hidden energy-saving responsibilities deserve more attentions. (3) Urban HIEC is more complicated than rural HIEC, and the first four PLs (PL⁰, PL¹, PL² and PL³), especially PL⁰, are the most important contributors to HIEC. (4) For PL⁰, only 11, 11 and 9 paths result in significant energy-saving for total, urban and rural HIEC, respectively. (5) Energy management for high-order PLs is sector-dependent and should consider the formation, length, and magnitude of the key paths.

© 2018 Elsevier B.V. All rights reserved.

1. Introduction

Energy consumption is the dominant contributor to climate change, accounting for approximately 60% of global greenhouse gas (GHG) emissions (Guo et al., 2016). More specifically, household energy consumption is a growing source of GHG emissions among different energy consumption categories (Bin and Dowlatabadi, 2005; Druckman and Jackson, 2009; Zhu et al., 2012; Wiedenhofer et al., 2017). In China, household energy consumption is the second largest energy consumption category behind the industrial category (Zhao et al., 2012). Over the past three decades, energy consumption in Chinese households has increased rapidly, at an annual growth rate of 9.42% (Fan et al., 2017). Domestic demand has restructured the economy and China's household energy consumption is projected to continue to grow in the future (Zhu et al., 2012). Therefore, increasing energy-saving in Chinese households is critical to achieving long-term climate goals (Dietz et al., 2009; Werfel, 2017).

Household consume energy directly and indirectly. Direct energy consumption occurs when consumers use products for activities such as home heating, lighting, and cooking (Wei et al., 2007; Kerkhof et al., 2009). Indirect energy consumption refers to energy consumption during the production of goods and services, such as food and clothing (Park and Heo, 2007). In developed countries, household indirect energy consumption (HIEC) plays a dominant role in embodied household energy consumption (e.g., Lenzen et al., 2004; Park and Heo, 2007; Cellura et al., 2011; Ferguson and MacLean, 2011; Büchs and Schnepf, 2013). Wei et al. (2007) and Liu et al. (2009) found that HIEC accounts for approximately 62–84.56% of the embodied household energy consumption in China, a developing country. Therefore, saving in Chinese HIEC should be well addressed and constitute a target for uncovering energy-saving responsibility clearly.

Many studies have evaluated HIEC at a regional level, exploring how to assign energy-saving responsibilities based on different household characteristics, expenditures, and behaviours (e.g., Lenzen et al., 2004; Park and Heo, 2007; Wei et al., 2007; Liu et al., 2009; Ferguson and MacLean, 2011; Jalas and Juntunen, 2015). These studies have significantly contributed to conceptualizing and quantifying energy-saving responsibilities from the perspective of final consumption. However, households consume a large variety of goods and services. Evaluating HIEC from a sectoral perspective can help clarify the sources of energy consumption and formulate targeted energy-saving policies. Previous studies have not assessed HIEC from a sectoral perspective or quantified

^{*} Corresponding author at: Department of Management Science, College of Management, Shenzhen University, Shenzhen 518060, China.

E-mail address: qinquande@gmail.com (Q. Qin).

the energy-saving responsibility in different stages (i.e. production layers, PLs) along the production chains.

Quantifying energy-saving responsibilities associated with HIEC requires considering entire supply chains (i.e., from producers to consumers) and decomposing the potential energy-saving contributions of different PLs (Skelton et al., 2011; Skelton, 2013; Zhang et al., 2017). Producing household goods and services involves multiple energy-intensive sectors at different PLs along supply chains (Guo et al., 2012). For example, private cars and household appliances cannot be produced without the metals smelting and pressing, the rubber and plastic production industries provide raw materials. These sectors are typically energy-intensive (Liu et al., 2012b). Without taking these cases into account, households cannot effectively and efficiently reduce energy consumption or adapt to climate change policies (Liu et al., 2012a). Therefore, implementing sector-focused energy-saving measures and evaluating the energy-saving potential of different PLs are important to improving the efficiency of energy conservation policies (Fan et al., 2017).

Structural path analysis (SPA) is an input-output technique that enables the tracing of linkages between producers and consumers to extract and rank the most important flows with respect to environmental impacts in an economy (Lenzen, 2003, 2007; Lenzen and Murray, 2010). SPA has been used extensively to map the energy consumption flows of different PLs and can provide useful information to policy-makers (e.g., Hong et al., 2016; Wang et al., 2016). However, previous studies using SPA only ranked paths based on the quantity of energy consumption; these studies did not identify the key paths with greater energysaving potential in the supply chains at a high resolution. While there are an infinite number of energy consumption paths in any economy, not every path is cost-effective. A sensitivity analysis can be used to identify key sectors and inter-sector flows with the highest potential for energy-saving (Tarancon and Río, 2012; Mattila, 2012; Wilting, 2012; Mattila et al., 2013; Meng et al., 2014). The resulting inter-sector flows include all the paths between the identified origin sectors (providing sectors) and the destination sectors (using sectors). The main weakness of a sensitivity analysis is that it cannot decompose the energy-saving potential among different PLs. The energy consumption paths can be infinitely long and infinitely numerous from any origin sector to the destination sectors: the longer the path, the smaller the value (Lenzen and Murray, 2010; Hong et al., 2016). Therefore, SPA and sensitivity analysis should be combined to formulate efficient energy-saving policies and target the energy-saving responsibilities of key sectors and key paths

Given the limitations described above, SPA and sensitivity analysis were used with an environmental input-output (EEIO) model to analyse regional HIEC. Guangdong Province in China was selected as the case study for three reasons. First, China's regional economies have experienced imbalanced development. As such, it is important to examine regional HIEC characteristics to develop energy-saving policies. Guangdong Province is one of China's most economically developed regions and has the country's highest residential income levels and consumption levels (NBSC, 2013). Second, Guangdong Province has the largest gross population and has experienced rapid urbanization; the urbanization rate increased from 39.3% in 1995 to 67.4% in 2012 (SBG, 1996, 2013). The province's large population and rapid urbanization have led to rapid growth in household energy requirements (Fan et al., 2017). Third, the Pearl River Delta in Guangdong Province is one of China's richest urban areas, with considerable energy consumption-related household carbon emissions (Wiedenhofer et al., 2017). Thus, Guangdong Province is expected to play a leading role in managing HIEC and can serve as an example for other regions.

This study combined an EEIO model with SPA and sensitivity analysis to examine regional HIEC from a sectoral perspective. The goal was to build an understanding of the allocation of energy-saving responsibilities among different sectors and different PLs. The study also identified key sectors and key paths that can lead to the assignment of responsibilities

for reducing HIEC in a cost-effective way. This provides insights to support decision-making related to mitigating HIEC in Guangdong Province and other regions in China.

The remainder of this paper is structured as follows. Section 2 describes the EEIO model, SPA, and sensitivity analysis for studying HIEC in Guangdong Province. Section 3 presents a description of the data used. The empirical results are discussed in Section 4. Finally, Section 5 presents the study's conclusions and policy implications.

2. Methods

2.1. EEIO model for household indirect energy consumption

This study applied an EEIO analysis as the basic method to quantify the indirect energy consumption required to meet final household energy demands in Guangdong Province. The EEIO analysis provides complete and systematic coverage of the entire indirect household energy consumption (Cellura et al., 2012; Zhu et al., 2012; Liu and Wu, 2013; Wiedenhofer et al., 2017). In the input-output analysis, the total output of one economy is expressed as follows:

$$\mathbf{X} = \mathbf{AX} + \mathbf{Y} \tag{1}$$

where **X** is the total output vector of an economy; **A** is the direct consumption coefficient matrix describing the relationship between all sectors of the economy; and **Y** is the final demand vector of the economy.

When solved, the output of Eq. (1) yields the following equation:

$$\mathbf{X} = (\mathbf{I} - \mathbf{A})^{-1} \mathbf{Y} \tag{2}$$

where **I** is the identity matrix and $(\mathbf{I} - \mathbf{A})^{-1}$ is the Leontief inverse, which has also been termed the complete demand coefficient matrix (Zhu et al., 2012).

The indirect energy consumption by households using the EEIO analysis is given by Eq. (3):

$$\mathbf{E} = \mathbf{e}(\mathbf{I} - \mathbf{A})^{-1} \mathbf{Y} \tag{3}$$

where **E** is the row vector of energy consumption from different industrial sectors for household consumption; **Y** is the diagonal matrix converted from the column vector of household consumption; and **e** is the diagonal matrix of the direct energy intensity of each sector in the input-output tables. Some recent studies have distinguished the direct consumption coefficient matrix **A** between domestic products and foreign imports. This quantifies the related emissions embodied in trade or the domestic supply chain (Li et al., 2016; Chen et al., 2017; Zhang et al., 2017). In this study, we aimed at uncovering the full picture of HIEC from a sectoral perspective in the current production structure and did not address the differences in energy intensities between domestic and import referring to the idea of Chang and Lahr (2016). The variable **e** is calculated as follows:

$$e_i = EC_i/X_i \tag{4}$$

where e_i is the direct energy intensity of sector i; EC_i is the production energy consumption for sector i; and X_i represents the total economic output from sector i.

2.2. Structural path analysis

By solving the Leontief inverse matrix in Eq. (3) using a Taylor series approximation, $\mathbf{X} = (\mathbf{I} - \mathbf{A})^{-1}$ can be written as follows (Skelton et al., 2011; Meng et al., 2015):

$$(I-A)^{-1} = I + A + A^2 + A^3 + \dots + A^t$$
 (5)

Eqs. (2) and (3) can be combined to trace chains of intermediate energy consumption through different PLs of a production system instigated by household consumption.

$$e(I-A)^{-1}Y = eIY + eAY + eA^2Y PL^2 + eA^3Y PL^3 + \dots + eA^tY$$
 (6)

where $\mathbf{eA^tY}$ is the energy consumption from the tth production layer (PL t). Therefore, the total indirect energy consumption instigated by household consumption can be expressed as follows:

$$E = \sum_{i,j=1}^{n} e_{i} \left(\delta_{ij} + a_{ij} + a_{ij}^{2} + a_{ij}^{3} + \cdots \right) y_{j}$$

$$= \sum_{i,j=1}^{n} e_{i} \left(\delta_{ij} + a_{ij} + \sum_{k=1}^{n} a_{ik} a_{kj} + \sum_{l=1}^{n} \sum_{k=1}^{n} a_{il} a_{lk} a_{kj} + \cdots \right) y_{j}$$

$$= \sum_{i=1}^{n} e_{i} y_{j} + \sum_{i=1}^{n} e_{i} \sum_{j=1}^{n} a_{ij} y_{j} + \sum_{i=1}^{n} e_{i} \sum_{k=1}^{n} a_{ik} \sum_{j=1}^{n} a_{kj} y_{j}$$

$$+ \sum_{i=1}^{n} e_{i} \sum_{l=1}^{n} a_{il} \sum_{k=1}^{n} a_{lk} \sum_{j=1}^{n} a_{kj} y_{j} + \cdots$$

$$(7)$$

where the subscripts i, j, k and l are the indices of sectors; E is the sum of the HIEC calculated using the EEIO model based on PL^0 from the input to the final product. This sum is represented by $e_i y_j$, which is added to the energy consumption in the higher-order production layers, such as the first-order production layer (PL^1) from sector i into sector j. This is represented by $e_i a_{ij} y_j$. A second-order production layer (PL^2) from sector i via sector k into sector k is represented by $e_i a_{ik} a_{kj} y_j$. To facilitate the distinction between PLs, energy consumption in the direct PL is defined as PL^0 . The energy consumption in higher-order PLs is defined as PL^1 to PL^∞ .

2.3. Sensitivity analysis of the EEIO model

This study applied the sensitivity analysis of the EEIO model, as proposed by Mattila (2012) and Mattila et al. (2013). This identified the most important sectors for household energy-saving in Guangdong Province. This sensitivity analysis systematically identified the key sectors and key inter-sector flows with more energy-saving potential (Meng et al., 2014), based on different components in the EEIO model (Mattila et al., 2013).

The EEIO model of Eq. (3) can be rewritten as a single equation (Leontief, 1970):

$$E = e(I - A)^{-1}Y = e\left(I + A + A^{2} + A^{3} + \dots + A^{t}\right)Y$$

$$= \underbrace{eIY}_{PL^{0}} + \underbrace{e\left(A + A^{2} + A^{3} + \dots + A^{t}\right)Y}_{PL^{1-\infty}}$$

$$= MY - eY$$
(8)

where **M** is the energy intensity multiplier matrix, which contains the life cycle energy intensities for all sectors; and **X** is the amount of total production needed to produce total household consumption **Y**.

Calculating the partial derivatives in Eq. (8) yields the following sensitivity indicators:

$$S_{e_q,\gamma} = \frac{\partial E_q/E_q}{\partial e_{q,\gamma}/e_{q,\gamma}} = X_{q,\gamma} \frac{e_{\gamma}}{E_q} \tag{9}$$

$$S_{a_q,\beta\gamma} = \frac{\partial E_q/E_q}{\partial a_{\beta\gamma}/a_{\beta\gamma}} = M_{\beta}X_{q,\gamma}\frac{a_{\beta\gamma}}{E_q} \tag{10}$$

$$S_{y_q,\beta} = \frac{\partial E_q/E_q}{\partial y_{q,\beta}/y_{q,\beta}} = M_\beta \frac{y_{q,\beta}}{E_q}$$
(11)

where the subscripts β and γ are the indices for sectors; subscript q separates the total, urban, and rural households; S_e denotes the sensitivity of direct energy intensities; S_y denotes the sensitivity of household demand; and S_a denotes the sensitivity of inter-sector input coefficients $(a_{\beta\gamma})$. When calculating S_a , the diagonal elements $(1-a_{\beta\beta})$ of S_a were scaled using the ratio $a_{\beta\beta}/(1-a_{\beta\beta})$ to determine the sensitivity of the original input coefficient. For this study, we selected 0.01 as the partition value to separate important parameters from less important parameters. This value indicates that a 100% change in a given component would influence the overall criteria by only 1%.

The input-output tables do not include causalities for production or consumption (Mattila et al., 2013). Controlling environmental impacts requires further consideration of the economic responsibilities of producers and consumers (Lenzen and Murray, 2010; Zhang, 2013). Therefore, because direct energy intensity (e) and household demand (y) were the main components of energy consumption in PL⁰ in Eq. (8), a key sector (or a key path) in PL⁰ can be characterized by the expression ($S_e > 0.01$) \cap ($S_y > 0.01$). Similarly, because direct energy intensity (e), inter-sector input-coefficients ($a_{\beta\gamma}$), and household demand (y) were the main components of energy consumption in higher PLs (PL^{1-\infty}), the expression ($S_e > 0.01$) \cap ($S_a > 0.01$) \cap ($S_y > 0.01$) reflects the key inter-sector flows with greater energy-saving potential for higher PLs (PL^{1-\infty}). Similar processing methods were used by Lenzen (2003) and Nagashima et al. (2016).

3. Data sources

This study's complexity called for a significant amount of data, including data for primary energy consumption, the gross output of different economic sectors, and the publicly available Guangdong Province input-output table. The Guangdong input-output tables were compiled by the Bureau of Guangdong Statistics every 5 years. The most recent version, published in 2012, contains 139 economic sectors and is derived from the Guangdong Statistical Yearbook (SBG, 2016). To maintain consistency between each sector's primary energy consumption data and the sector data in the Guangdong input-output table, the 2012 input-output table was aggregated into 45 sectors, as shown in supporting Table 1 of Appendix A. The 2012 sector-level primary energy consumption data for Guangdong Province were collected from the Guangdong Statistical Yearbook (SBG, 2013). Sector-level primary energy consumption is an aggregate indicator, measured in units of million tonnes of coal equivalent (Mtce).

4. Results and discussion

4.1. Household indirect energy consumption for different sectors

In 2012, the total HIEC in Guangdong Province was 111.15 Mtce, the rural HIEC was 14.45 Mtce, and the urban HIEC reached 96.70 Mtce. The urban level was 6.69 times the rural household level. Urban households included 67.4% of the total population of Guangdong Province in 2012 (SBG, 2013) and accounted for >86% of provincial HIEC. Rural households included 32.6% of the total provincial population and accounted for only 13% of provincial HIEC. This result is consistent with findings by Liu et al. (2009), who found large differences between the indirect energy consumption of urban and rural households in China.

One reason for this difference in HIEC is rapid urbanization (from 39.3% to 67.4% during 1995–2012) (SBG, 1996, 2013). The growing urban population requires more infrastructure construction and housing (Feng and Hubacek, 2016; Wiedenhofer et al., 2017). These requirements have induced significant additional indirect energy consumption (Liu et al., 2009; Feng and Hubacek, 2016). In addition,

differences in personal income account for some of the discrepancy between urban and rural HIEC (Hubacek et al., 2007; Golley and Meng, 2012; Perobelli et al., 2015; Feng and Hubacek, 2016; Wiedenhofer et al., 2017). The personal income of urban residents was 2.87 times the personal income of rural residents in Guangdong Provinces in 2012 (SBG, 2013).

Fig. 1 shows detailed components of HIEC for 45 sectors in Guangdong Province in 2012. There are significant disparities in the sectoral energy consumption. *Electricity and Steam Production and Supply* (S38), *Residential Services* (S45), and *Transport*, *Storage*, *Postal and Telecommunication Services* (S42) were the top energy consumption sectors, contributing a total of 26.47%, 26.04%, and 29.31% to the provincial total, urban and rural HIEC values, respectively. By individual component, energy consumption in PL⁰ was most important in 12, 13, and 10 sectors, respectively, for total, urban and rural household. Examples of relevant components include *Residential Services* (S45), *Other Services* (S44), and *Farming*, *Forestry*, *Animal Husbandry and Fishery* (S1).

It can be seen from Fig. 1 that the importance of several sectors in reducing HIEC may be underestimated from a final consumption perspective. For example, *Smelting and Pressing of Nonferrous Metals* (S26) and *Smelting and Pressing of Ferrous Metals* (S25) account for a considerable proportion (approximately 11.06%) of urban HIEC (Fig. 1) and all energy consumption occurred in $PL^{1\to\infty}$. This is because these sectors are major material processing sectors, providing intermediate products for other sectors to manufacture the commodities and services to meet the final demand of urban households. However, because urban households did not generate direct demand for these sectors, the energy consumption for these sectors for PL^0 was zero (Fig. 1). The final demand from households indirectly drives these

sectors to consume energy through the supply chain network in the economy. Therefore, the energy-saving potential within these sectors and the related supply chains is not negligible.

4.2. Household indirect energy consumption for different production layers

This study applied SPA to calculate the HIEC for different PLs in Guangdong Province in 2012 (see Table 1). Table 1 shows that approximately 79.38%, 78.76%, and 83.50% of total, urban, and rural HIEC are embedded in the first four PLs (PL^{0-3}); the change in the cumulative HIEC is smaller in $PL^{4-\infty}$. This result is consistent with Lenzen (2007), who found that the environmental load often decreases with an increased number of PLs in an economy. A set threshold is usually specified in the SPA process to terminate infinite paths (Huang et al., 2009; Llop and Ponce-Alifonso, 2015). Therefore, we focus on the potential household indirect energy-saving in these four PLs (PL^{0-3}) in Guangdong Province. This approach is more effective and efficient than investigating all possible stages (Yang et al., 2015; Hong et al., 2016; Wang et al., 2016).

This procedure is consistent with the conclusions of Lenzen (2003), who suggested that when conducting SPA using energy and emissions data, most of the large paths are of the zero-th or first order. Table 1 shows that PL 0 and PL 1 are responsible for >50% of HIEC. The embedded energy in PL 0 is higher than in other PLs, totalling approximately 33%, 32%, and 40% for total, urban, and rural HIEC, respectively, in Guangdong Province in 2012. This result indicates that managing energy consumption in PL 0 among different sectors is most important for conserving household indirect energy in Guangdong Province. In addition, the energy consumption in PL $^{0\to 3}$ accounts for 78.76% of indirect energy consumption for urban households, which is lower than the energy

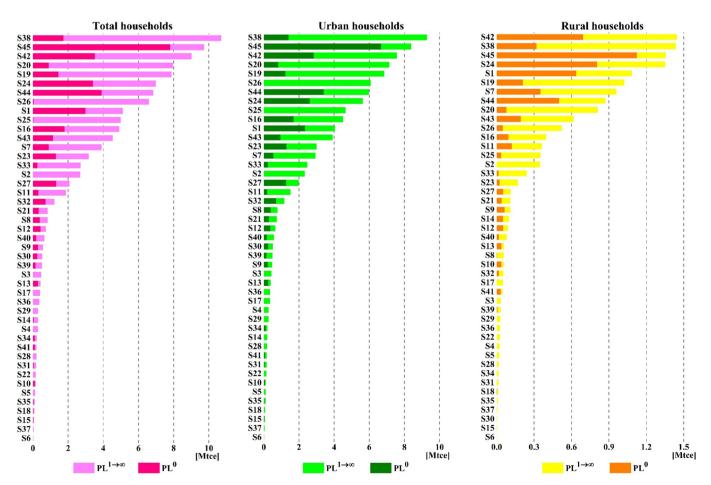


Fig. 1. HIEC in different sectors in Guangdong Province in 2012.

Table 1Summary of HIEC in different PLs.

		PL ⁰	PL ¹	PL^2	PL^3	PL^4	PL ⁵	$PL^{6\to\infty}$
Total households	Energy consumption (Mtce)	36.62	24.05	16.55	11.01	7.34	4.94	10.64
	Proportion (%)	32.94	21.64	14.89	9.91	6.61	4.44	9.57
	Cumulative proportion (%)	32.94	54.58	69.47	79.38	85.98	90.43	100
Urban households	Energy consumption (Mtce)	30.91	20.92	14.57	9.77	6.54	4.42	9.58
	Proportion (%)	31.96	21.63	15.07	10.10	6.77	4.57	9.9
	Cumulative proportion (%)	31.96	53.59	68.66	78.76	85.53	90.10	100
Rural households	Energy consumption (Mtce)	5.71	3.14	1.98	1.25	0.80	0.52	1.06
	Proportion (%)	39.51	21.70	13.67	8.62	5.53	3.61	7.36
	Cumulative proportion (%)	39.51	61.21	74.88	83.50	89.03	92.64	100

consumption in the first four PLs for rural households (83.50%). This implies that the energy consumption of urban household is more complex than for rural households. It is because that there is the "long tail" phenomenon of urban HIEC in Guangdong Province (Lenzen and Treloar, 2002; Huang et al., 2009).

4.3. Sensitivity analysis for different components

Table 2 presents the direct energy intensity sensitivity of key sectors (S_e) for HIEC in Guangdong Province in 2012. For total, urban, and rural households, there were 19, 19 and 17 main components of direct energy intensity, respectively. For total household energy, the direct energy intensity of *Electricity and Steam Production and Supply* (S38) had the highest sensitivity index $(S_e=0.096)$. This indicates that every 1% reduction in direct energy intensity for *Electricity and Steam Production and Supply* (S38) will reduce energy consumption by 0.096% for all households.

For urban households, the direct energy intensities for *Electricity and Steam Production and Supply* (\$38), *Residential Services* (\$45), and *Transport, Storage, Postal and Telecommunication Services* (\$42) had the highest sensitivity indices (ranging between 0.078 and 0.096). These sectors were followed by *Raw Chemical Materials and Chemical Products* (\$20), *Petroleum Processing, Coking and Nuclear Fuel Processing* (\$19), *Smelting and Pressing of Nonferrous Metals* (\$26), *Other Services* (\$44), and *Nonmetal Mineral Products* (\$24) (with sensitivity indices between 0.058 and 0.074).

For rural households, the direct energy intensities for *Transport*, *Storage*, *Postal and Telecommunication Services* (S42), *Electricity and Steam Production and Supply* (S38), *Residential Services* (S45), and *Nonmetal Mineral Products* (S24) had the highest sensitivity indices (ranging from 0.093 to 0.100). These sectors were followed by *Farming*, *Forestry*,

Table 2 Major components of S_e for HIEC in Guangdong Province in 2012.

Consumption sector	Total households	Urban households	Rural households
S1	0.046	0.042	0.075
S2	0.024	0.024	0.024
S7	0.035	0.030	0.066
S11	0.017	0.016	0.025
S16	0.044	0.046	0.027
S19	0.071	0.071	0.071
S20	0.071	0.074	0.056
S23	0.028	0.031	0.012
S24	0.063	0.058	0.093
S25	0.045	0.048	0.024
S26	0.059	0.063	0.036
S27	0.019	0.020	_
S32	0.011	0.012	_
S33	0.024	0.025	0.016
S38	0.096	0.096	0.099
S42	0.081	0.078	0.100
S43	0.041	0.040	0.043
S44	0.062	0.062	0.060
S45	0.087	0.087	0.094

Numbers in bold indicates the sensitivity indicator values are greater than 0.05.

Animal Husbandry and Fishery (S1), Petroleum Processing, Coking and Nuclear Fuel Processing (S19), Food Processing (S7), Other Services (S44), and Raw Chemical Materials and Chemical Products (S20) (ranging from 0.056 to 0.075).

Some major components of S_e were common to both urban and rural households. For example, S_e exceeded 0.08 for the direct energy intensities of *Electricity and Steam Production and Supply* (S38) and *Residential Services* (S45). However, some major components of S_e were higher for rural households than for urban households. For example, the S_e for *Farming, Forestry, Animal Husbandry and Fishery* (S1) and *Food Processing* (S7) in urban households was lower than 0.05, but exceeded 0.05 in rural households (ranging from 0.066 to 0.075).

Eq. (10) shows how the sensitivity was calculated for the inter-sector input coefficients ($a_{\beta\gamma}$) of HIEC. Eq. (8) indicates that the inter-sector input-coefficients affect energy consumption for the higher-order PLs (PL^{1-\infty}). This means that enhancing energy conservation in PL^{1-\infty} for HIEC in Guangdong Province requires examining the S_a values of different production sectors. The S_a results indicate that of 6075 economic interactions, only 30, 30 and 28 were important (S_a > 0.01) for the total, urban and rural HIEC in Guangdong Province in 2012 (Fig. 2). This result implies that managing HIEC for the higher-order PLs (PL^{1-\infty}) for urban households is more difficult than for rural households. In addition, there were more paths for reducing indirect energy consumption in high PLs in urban households, compared to rural households.

The interactions with the most significant effects included: Raw Chemical Materials and Chemical Products → Raw Chemical Materials and Chemical Products (S20 \rightarrow S20) ($S_a = 0.082, 0.085$), Smelting and Pressing of Nonferrous Metals → Smelting and Pressing of Nonferrous Metals (S26 \rightarrow S26) ($S_a = 0.257, 0.272$) and Electronic and Telecommunications Equipment → Electronic and Telecommunications Equipment $(S33 \rightarrow S33)$ ($S_a = 0.270, 0.283$), while Electricity and Steam Production and Supply → Electricity and Steam Production and Supply (S38 → S38) $(S_a = 0.054, 0.054)$ had less significant effects for total and urban HIEC, especially for urban households. This is because indirect energy consumption by urban households accounted for the largest proportion (approximately 86%) of total HIEC in Guangdong Province in 2012. Unlike the total and urban households, the interactions between Smelting and Pressing of Nonferrous Metals → Smelting and Pressing of Nonferrous Metals (S26 \rightarrow S26) ($S_a = 0.156$) and Electronic and $Telecommunications \ Equipment \rightarrow Electronic \ and \ Telecommunications$ Equipment (S33 \rightarrow S33) ($S_a = 0.184$) were the most significant for rural HIEC; Food Processing → Farming, Forestry, Animal Husbandry and Fishery (S7 \rightarrow S1) ($S_a = 0.063$), Raw Chemical Materials and Chemical Products → Raw Chemical Materials and Chemical Products (S20 → S20) $(S_a = 0.064)$ and Electricity and Steam Production and Supply \rightarrow Electricity and Steam Production and Supply (S38 \rightarrow S38) ($S_a = 0.056$) were less significant for rural HIEC.

This result is consistent with the conclusions of Yan et al. (2016). The most sensitive interactions involved self-supplied intermediate products consumed by the sectors themselves, such as Raw Chemical Materials and Chemical Products \rightarrow Raw Chemical Materials and Chemical Products (S20 \rightarrow S20), Smelting and Pressing of Nonferrous Metals \rightarrow Smelting and Pressing of Nonferrous Metals (S26 \rightarrow S26),

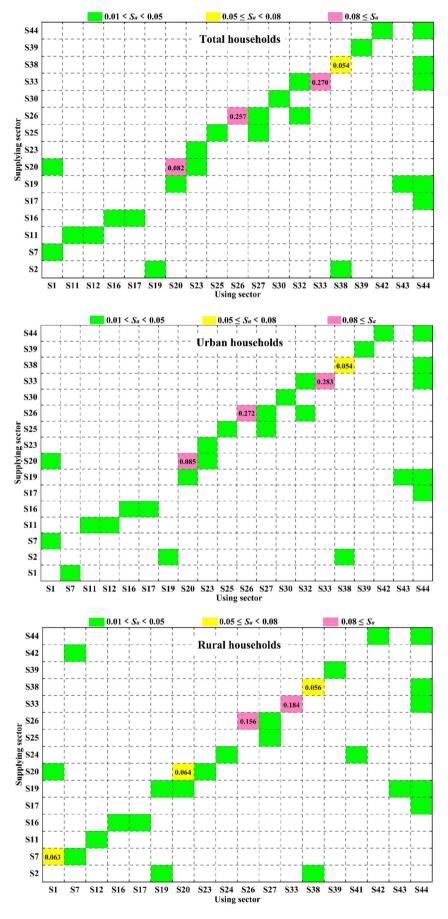


Fig. 2. Main components of S_a for HIEC in Guangdong Province in 2012.

Electronic and Telecommunications Equipment \rightarrow Electronic and Telecommunications Equipment (S33 \rightarrow S33) and Electricity and Steam Production and Supply \rightarrow Electricity and Steam Production and Supply (S38 \rightarrow S38), with the exception of Food Processing \rightarrow Farming, Forestry, Animal Husbandry and Fishery (S7 \rightarrow S1) for rural households in Guangdong Province. All these sectors are pollution-intensive industrial sectors in Guangdong Province (Ou et al., 2017). Thus, advancing production technologies in these sectors could realize significant energy-saving potential and pollution reduction co-benefits for households in Guangdong Province. The S_a value derived from the Leontief inverse reflects the energy-saving potential of advancing production technology (Jiang et al., 2015).

Based on Eq. (11), Table 3 presents the major components of the sensitivity of final demand (S_v) for HIEC in Guangdong Province in 2012. For household demand, we found high sensitivities with respect to Metal Products (S27), Other Services (S44), and Residential Services (S45) for total HIEC (0.097–0.140), and lower sensitivities with respect to Farming, Forestry, Animal Husbandry and Fishery (S1), Rubber and Plastic Products (S23), Nonmetal Mineral Products (S24), and Electric Equipment and Machinery (S32) (0.056–0.076). The sensitivity of both urban and rural household demand was dominated by a few major components with high sensitivities. For example, Metal Products (S27), Other Services (S44), and Residential Services (S45) have very high sensitivities (0.099-0.141) for urban household demand, followed by Farming, Forestry, Animal Husbandry and Fishery (S1), Rubber and Plastic Products (S23), Nonmetal Mineral Products (S24), and Electric Equipment and Machinery (S32) (0.049-0.077). Similarly, rural household demand was highly sensitive to Farming, Forestry, Animal Husbandry and Fishery (S1), Nonmetal Mineral Products (S24), Other Services (S44), and Residential Services (S45) (0.101–0.138). These were followed by Food Processing (S7) ($S_v = 0.074$) and Transport, Storage, Postal and Telecommunication Services (S42) ($S_v = 0.069$). These findings are reflected as high sensitivities for both the urban and rural household demand of Farming, Forestry, Animal Husbandry and Fishery (S1), Other Services (S44), and Residential Services (S45).

The analysis above identifies the most important sectors for energy-savings associated with HIEC in Guangdong Province based on the different components of input-output analysis. These highlight initial directions for reducing HIEC at a sector level. Examples include increasing energy efficiency by improving energy-related technology and production technology. These improvements would reduce sector-level direct energy intensities and energy consumption during the production process (Jiang et al., 2015). However, during the actual production process, energy consumption in different PLs within the context of a Leontief input-output (IO) model is determined by the final demand for households, along with the sectoral direct energy intensity and the inter-sector input coefficients (Skelton et al., 2011). Therefore, combining these three components to find the paths with the highest energy-saving potential provides more information for policy-makers.

4.4. Key paths for energy-saving in PL⁰

Fig. 3 shows the proportion of energy consumption for PL⁰ for HIEC in Guangdong Province in 2012. The grey shading indicates the key paths responsible for energy-saving in PL⁰, where $(S_e > 0.01) \cap (S_y > 0.01)$. Some paths are sensitive to energy consumption in PL⁰; however, the energy consumption of these paths in PL⁰ is not significant and focusing on energy saving along these paths may not be economically effective. For example, *Electronic and Telecommunications Equipment* (S33) is sensitive for total HIEC in PL⁰ (Fig. 4). However, the energy consumption in *Electronic and Telecommunications Equipment* (S33) only accounts for 0.724% of energy consumption in PL⁰ for total households. This value is significantly lower than consumption in *Garments and Other Fiber Products* (S12) (1.18%), which is not sensitive for total HIEC in PL⁰.

To reduce HIEC in PL⁰, policy-makers should consider the differences in the magnitude of energy consumption paths in PL⁰ and adopt

Table 3 Main components of S_v for HIEC in Guangdong Province in 2012.

Consumption sector	Total households	Urban households	Rural households
S1	0.076	0.069	0.125
S7	0.025	0.017	0.074
S8	0.018	0.021	-
S9	0.014	0.013	0.025
S10	-	-	0.014
S11	-	-	0.024
S12	0.025	0.026	0.024
S13	0.015	0.015	0.015
S16	0.038	0.042	0.016
S19	0.025	0.024	0.028
S20	0.027	0.028	0.018
S21	0.0101	0.0102	-
S23	0.056	0.063	-
S24	0.056	0.049	0.101
S26	-	-	0.014
S27	0.097	0.107	0.030
S30	0.022	0.026	-
S32	0.068	0.077	0.013
S33	0.021	0.023	0.011
S38	0.033	0.031	0.047
S41	0.0101	-	0.022
S42	0.046	0.042	0.069
S43	0.026	0.025	0.034
S44	0.140	0.141	0.138
S45	0.101	0.099	0.112

Numbers in bold indicates the sensitivity indicator values are greater than 0.05.

appropriate energy-saving policies for different paths. To do this, we set 2.70%, 2.86% and 2.86% as the threshold values, which are the average proportion of energy consumption in PL⁰ for total, urban, and rural households, respectively, in Guangdong Province. The paths greater than the average proportion in Fig. 4 have greater energy-saving potential. There were 11, 11, and 9 paths with this greater potential to save energy for total, urban, and rural households, respectively (Fig. 3). The key paths with greater potential for reducing HIEC in PL⁰ account for 83.23%, 83.49%, and 84.93% of the energy consumption in PL⁰ for total, urban, and rural households, respectively, in Guangdong Province in 2012.

Similarly, because direct energy intensity (e) and household demand (y) were the main components of energy consumption in PL⁰, the energy-saving policies for these key paths should differ. Using urban household as an example, compared with S_e and S_v , the S_e of the following paths were higher than S_v among the key paths in PL⁰: Transport, Storage, Postal and Telecommunication Services (S42), Nonmetal Mineral Products (S24), Papermaking and Paper Products (S16), Electricity and Steam Production and Supply (S38), Petroleum Processing, Coking and Nuclear Fuel Processing (S19), and Wholesale, Retail Trade and Catering Services (S43) (Fig. 3). This suggests that better managing direct energy intensities for these sectors will significantly decrease the embodied energy in PL⁰ for total households in Guangdong Province. S_v was larger than S_e for Residential Services (S45), Other Services (S44), Farming, Forestry, Animal Husbandry and Fishery (S1), Metal Products (S27), and Rubber and Plastic *Products* (S23). Therefore, reducing energy consumption in these sectors should focus on improving residential awareness of energy conservation and advocating rational consumption towards more sustainable living practices (Feng et al., 2009; Wiedenhofer et al., 2017).

4.5. Key paths for energy-saving in higher PLs

Table 1 shows that a significant proportion of the HIEC in Guangdong Province was consumed in the higher PLs $(PL^{1\to\infty})$. Supporting Fig. 1 in Appendix A shows the components of sectoral energy consumption in higher PLs $(PL^{1\to\infty})$ for HIEC in Guangdong Province in 2012. The figure indicates that the most energy was consumed in PL $^{1\to3}$. This makes managing the energy consumption in these production layers particularly important.

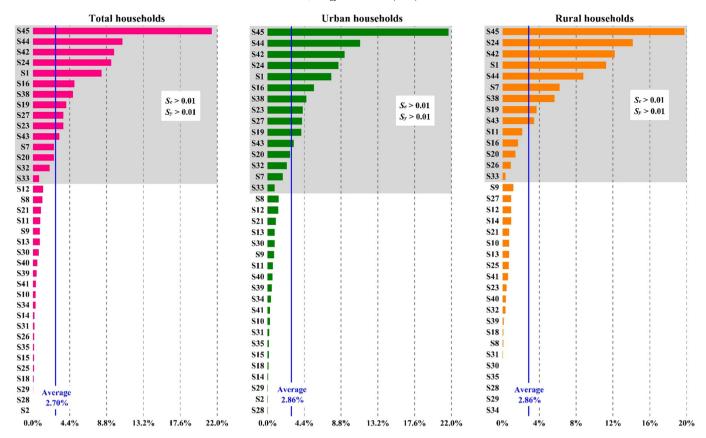


Fig. 3. Components of energy consumption in PL⁰ for HIEC in Guangdong Province in 2012.

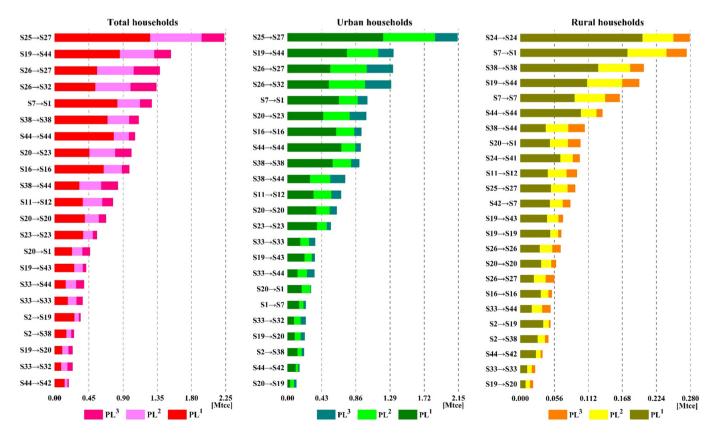


Fig. 4. Key inter-sector flows of energy consumption in $PL^{1\rightarrow 3}$ for HIEC in Guangdong Province in 2012.

Fig. 4 shows the key inter-sector flows (i.e. $(S_e > 0.01) \cap (S_a > 0.01) \cap$ $(S_v > 0.01)$) of energy consumption in PL¹⁻³ for HIEC in Guangdong Province in 2012. The figure indicates that there are 22, 23 and 24 crucial inter-sector flows. The total energy consumption in these inter-sector flows accounts for 34.12%, 35.05% and 37.95% of the total, urban, and rural HIEC in $PL^{1\rightarrow3}$, respectively. Thus, these key intersector flows present the highest energy-saving potential for HIEC in PL^{1→3} in Guangdong Province. However, some hidden inter-sector flows should be addressed to save energy in higher PLs. For example, Smelting and Pressing of Nonferrous Metals (S26) and Smelting and Pressing of Ferrous Metals (S25) were identified as crucial hidden sectors impacting urban HIEC (Fig. 1). Some hidden flows related to these two sectors (Smelting and Pressing of Ferrous Metals → Metal Products (S25 → S27), Smelting and Pressing of Nonferrous Metals → Metal Products (S26 → S27) and Smelting and Pressing of Nonferrous Metals → Electric Equipment and Machinery (S26 \rightarrow S32)) are key inter-sector flows responsible for urban household indirect energy savings.

Fig. 4 recommends priorities for managing energy consumption in key inter-sector flows in different PLs. For example, *Raw Chemical Materials and Chemical Products* \rightarrow *Petroleum Processing, Coking and Nuclear Fuel Processing* (S20 \rightarrow S19) and *Other Services* \rightarrow *Other Services* (S44 \rightarrow S44) are the two key inter-sector flows for urban households. For *Raw Chemical Materials and Chemical Products* \rightarrow *Petroleum Processing, Coking and Nuclear Fuel Processing* (S20 \rightarrow S19), most energy is consumed in PL², accounting for 41.29% of this key inter-sector flow. For *Other Services* \rightarrow *Other Services* (S44 \rightarrow S44), most energy is consumed in PL¹, accounting for 73.97% of this inter-sector flow. Thus, priority should be given to PL² to reduce the energy consumption for *Raw Chemical Materials and Chemical Products* \rightarrow *Petroleum Processing, Coking and Nuclear Fuel Processing* (S20 \rightarrow S19). In contrast, to manage the energy consumed in PL¹, it would be more productive to address *Other Services* \rightarrow *Other Services* (S44 \rightarrow S44).

The sensitivity analysis can help policy-makers determine the key inter-sector flows for the higher-order PLs (PL¹⁻³) (see Fig. 4). However, all key inter-sector flows had a large number of paths. Thus, SPA was used to understand energy flows and to determine energy consumption paths and management priorities for each key inter-sector flow in PL¹⁻³. The top energy consumption paths in PL¹⁻³ for total, urban and rural households in Guangdong Province are shown in Supporting Tables 2–4 in Appendix A; shading indicates the key paths where $(S_e > 0.01) \cap (S_a > 0.01) \cap (S_v > 0.01)$.

Supporting Tables 2–4 in Appendix A suggest that significant opportunities for energy conservation may be sector-dependent. Using total households as an example, from a production-oriented perspective, the key paths can be traced to five industry sectors: Smelting and Pressing of Nonferrous Metals (S26), Smelting and Pressing of Ferrous Metals (S25), Petroleum Processing, Coking and Nuclear Fuel Processing (S19), Raw Chemical Materials and Chemical Products (S20), and Electricity and Steam Production and Supply (S38)). Paths related to these sectors contributed 21.71% of the embodied energy for $PL^{1\rightarrow3}$ (Supporting Table 2 in Appendix A). Moreover, these paths appeared to be evenly distributed across PLs, because of the complex economic relationships among different industrial sectors (Zhang et al., 2017). From a consumption-oriented perspective, the key paths were mainly concentrated in two sectors (Other Services (S44) and Metal Products (S27)). Together, these contributed 14.26% of the embodied energy for $PL^{1\rightarrow3}$ (Supporting Table 2 in Appendix A). Therefore, technical improvements (Li, 2010) and energy structure adjustments (Zhu et al., 2015) could drive these sectors to reduce energy consumption in $PL^{1\rightarrow 3}$, reducing total HIEC in Guangdong Province.

Supporting Tables 2–4 in Appendix A also indicate that managing energy consumption for the total households should prioritize key paths with "self-circular flow" (i.e., flow that starts and ends in the same sector), such as *Other Services* \rightarrow *Other Services* (S44 \rightarrow S44), *Smelting and Pressing of Ferrous Metals* \rightarrow *Smelting and Pressing of Ferrous Metals* \rightarrow *Metal Products* (S25 \rightarrow S25 \rightarrow S27), *Smelting and Pressing of Ferrous Metals*

Ferrous Metals \rightarrow Metal Products \rightarrow Metal Products (S25 \rightarrow S27 \rightarrow S27), and Electricity and Steam Production and Supply \rightarrow Electricity and Steam Production and Supply \rightarrow Electricity and Steam Production and Supply (S38 \rightarrow S38) (Supporting Table 1). Energy consumers in the same sector have similar energy consumption patterns. As such, if one sector can successfully engage its immediate suppliers and encourage them to influence their suppliers, it can create a ripple effect (Skelton, 2013). Therefore, prioritizing this type of paths could improve energy management efficiency and reduce management costs.

Supporting Tables 2–4 in Appendix A suggests that key energy consumption paths reflect the complexity levels of various inter-sector flows. For urban household, with energy consumption of 1.00 and 0.99 Mtce, respectively (Fig. 4). For Food Processing → Farming, Forestry, Animal Husbandry and Fishery (S7 \rightarrow S1), two paths (Food Processing \rightarrow Farming, Forestry, Animal Husbandry and Fishery (S7 → S1) and Food Processing → Food Processing → Farming, Forestry, Animal Husbandry and Fishery (S7 \rightarrow S7 \rightarrow S1)) consumed >0.1 Mtce, accounting for 80.98% of energy consumption in this key inter-sector flow. For Raw Chemical Materials and Chemical Products \rightarrow Rubber and Plastic Products (S20 \rightarrow S23), three key paths (Raw Chemical Materials and Chemical Products → Rubber and Plastic Products (S20 → S23), Raw Chemical Materials and Chemical *Products* → *Raw Chemical Materials and Chemical Products* → *Rubber and* Plastic Products (S20 → S20 → S23) and Raw Chemical Materials and Chemical Products → Rubber and Plastic Products → Rubber and Plastic Products (S20 \rightarrow S23 \rightarrow S23)) consumed >0.1 Mtce, accounting for 78.64% of the energy consumption in this key inter-sector flow. Thus, the energy consumption paths for inter-sector flows of Raw Chemical Materials and Chemical Products → Rubber and Plastic Products (S20 \rightarrow S23) are more diffuse and more complex than Food Processing \rightarrow Farming, Forestry, Animal Husbandry and Fishery (S7 \rightarrow S1).

5. Conclusions and policy implications

This study developed a profile for energy-saving responsibilities associated with HIEC among different sectors and the related paths in Guangdong Province in 2012. SPA and sensitivity analysis were combined to determine the key sectors and key paths between different production layers with the highest energy-saving potential. The main conclusions of this study are as follows.

The total HIEC in Guangdong Province in 2012 was 111.15 Mtce. There were significant differences in HIEC between urban and rural households. More than 86% of the total HIEC in Guangdong Province came from urban areas, with only 13% coming from rural areas. The *Electricity and Steam Production and Supply* (S38), *Transport, Storage, Postal and Telecommunication Services* (S42), and *Residential Services* (S45) sectors were the main drivers for both urban and rural HIEC in Guangdong Province in 2012. However, the results indicate that a considerable proportion of HIEC was associated with material processing sectors, including *Smelting and Pressing of Nonferrous Metals* (S26) and *Smelting and Pressing of Ferrous Metals* (S25) (for urban households). This indicates that these sectors should be prioritized because of their hidden responsibilities to reduce provincial HIEC.

The patterns of energy consumption in different PLs and their contributions to HIEC indicate that the first four PLs (PL^{0-3}) had the most energy-saving potential compared to higher-order PLs ($PL^{4-\infty}$) in Guangdong Province for both urban and rural households. A sensitivity analysis was used to identify the key sectors and key internal relationships between the different components (including direct energy intensities, inter-sector input coefficients, and final demand) having the greatest impact on the total, urban, and rural HIEC. With respect to sectoral direct energy intensity, *Transport*, *Storage*, *Postal and Telecommunication Services* (S42), *Electricity and Steam Production and Supply* (S38), and *Petroleum Processing*, *Coking and Nuclear Fuel Processing* (S19) had the highest sensitivities; *Other Services* (S44) and *Residential Services* (S45) were most sensitive to the final demand for total, urban, and rural households in Guangdong Province. For the inter-sector

input coefficients, the most sensitive interactions were associated with self-supplied intermediate products consumed by sectors themselves, such as Raw Chemical Materials and Chemical Products \rightarrow Raw Chemical Materials and Chemical Products (S20 \rightarrow 20), Smelting and Pressing of Nonferrous Metals \rightarrow Smelting and Pressing of Nonferrous Metals (S26 \rightarrow S26), Electronic and Telecommunications Equipment \rightarrow Electronic and Telecommunications Equipment (S33 \rightarrow S33) and Electricity and Steam Production and Supply \rightarrow Electricity and Steam Production and Supply (S38 \rightarrow S38) for rural households.

We determined the critical energy-saving paths for different PLs by combining SPA with the sensitivity analysis for direct energy intensities, inter-sector input coefficients, and final demand. When examining key paths in PL⁰, policy-makers should consider the sensitivity of all paths and the actual energy consumption for each path. Energy consumption is low for some paths in PL⁰; as such, it is inefficient to attempt to save energy along these paths. There are only 11, 11, and 9 crucial paths in PL⁰ for total, urban, and rural households in Guangdong Province, respectively. These have the greatest energy-saving potential compared to other paths.

For the HIEC from $PL^{1\to 3}$, we identified 22, 23, and 24 crucial intersector flows, accounting for 34.12%, 35.05%, and 37.95% of the total, urban, and rural HIEC, respectively. In addition, several hidden intersector flows in higher-order PLs should be examined for their potential to increase energy-saving. These include the flows from *Smelting and Pressing of Ferrous Metals* \rightarrow *Metal Products* (S25 \rightarrow S27), *Smelting and Pressing of Nonferrous Metals* \rightarrow *Metal Products* (S26 \rightarrow S27) and *Smelting and Pressing of Nonferrous Metals* \rightarrow *Electric Equipment and Machinery* (S26 \rightarrow S32); these flows begin in the crucial hidden sectors *Smelting and Pressing of Nonferrous Metals* (S26) and *Smelting and Pressing of Ferrous Metals* (S25) for urban households. Although every inter-sector flow includes an infinite number of key paths, energy-saving measures for key paths may be sector-dependent and should be determined based on the form, length, and magnitude of the paths.

The results of this study highlight three key policy implications. First, comprehensively assessing inter-sector linkages will help clarify which key sectors have significant energy-saving potential. Implementing energy-saving measures in these key sectors will contribute to reducing energy consumption across the economic system. Second, improving energy efficiency in some key sectors, especially for PL⁰ and self-supplied higher PLs, is important to reduce HIEC. It can be achieved by developing energy efficient and cleaner technologies. In this case, it is urgent to increase the degree of industrial concentration and close down outdated production facilities. Third, cross-sectoral collaboration is critically important for higher PLs' paths with strong sectoral heterogeneity. For these paths, cross-sectoral collaboration strengthens the ripple effect among sectors along the supply chains.

Acknowledgements

The authors thank anonymous referees and an editor of this journal for their valuable comments and gratefully acknowledge the assistance of Prof. Tuomas Mattila for constructive suggestions for the sensitivity analysis used in this study. The work is partly supported by China Postdoctoral Science Foundation Funded Project (No. 2017M620381), National Natural Science Foundation of China (Nos. 71521002 and 71402103), National Social Science Fund of China (No. 15CJL042), Natural Science Foundation of Guangdong Province (No. 2015A030313556) and Natural Science Foundation of Zhejiang Province (No. LQ17G030004).

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.eneco.2018.05.006.

References

- Bin, S., Dowlatabadi, H., 2005. Consumer lifestyle approach to US energy use and the related CO₂ emissions. Energy Policy 33 (2), 197–208.
- Büchs, M., Schnepf, S.V., 2013. Who emits most? Associations between socio-economic factors and UK households' home energy, transport, indirect and total CO₂ emissions. Ecol. Econ. 90, 114–123.
- Cellura, M., Longo, S., Mistretta, M., 2011. The energy and environmental impacts of Italian households consumptions: an input-output approach. Renew. Sust. Energ. Rev. 15 (8) 3897–3908
- Cellura, M., Longo, S., Mistretta, M., 2012. Application of the structural decomposition analysis to assess the indirect energy consumption and air emission changes related to Italian households consumption. Renew. Sust. Energ. Rev. 16 (2), 1135–1145.
- Chang, N., Lahr, M.L., 2016. Changes in China's production-source CO₂ emissions: insights from structural decomposition analysis and linkage analysis. Econ. Syst. Res. 28 (2), 1–19.
- Chen, B., Li, J.S., Chen, G.Q., Wei, W.D., Yang, Q., Yao, M.T., Shao, J.A., Zhou, M., Xia, X.H., Dong, K.Q., Xia, H.H., Chen, H.P., 2017. China's energy-related mercury emissions: characteristics, impact of trade and mitigation policies. J. Clean. Prod. 141, 1259–1266
- Dietz, T., Gardner, G.T., Gilligan, J., Stern, P.C., Vandenbergh, M.P., 2009. Household actions can provide a behavioral wedge to rapidly reduce US carbon emissions. Proc. Natl. Acad. Sci. U. S. A. 106 (44), 18452–18456.
- Druckman, A., Jackson, T., 2009. The carbon footprint of UK households 1990–2004: a socio-economically disaggregated, quasi-multi-regional input-output model. Ecol. Econ. 68 (7), 2066–2077.
- Fan, J.L., Zhang, Y.J., Wang, B., 2017. The impact of urbanization on residential energy consumption in China: an aggregated and disaggregated analysis. Renew. Sust. Energ. Rev. 75, 220–233.
- Feng, K.S., Hubacek, K., 2016. Carbon implications of China's urbanization. Energy Ecol. Environ. 1 (1), 39–44.
- Feng, K.S., Hubacek, S., Guan, D.B., 2009. Lifestyles, technology and $\rm CO_2$ emissions in China: a regional comparative analysis. Ecol. Econ. 69 (1), 145–154.
- Ferguson, T.M., MacLean, H.L., 2011. Trade-linked Canada-United States household environmental impact analysis of energy use and greenhouse gas emissions. Energy Policy 39 (12), 8011–8021.
- Golley, J., Meng, X., 2012. Income inequality and carbon dioxide emissions: the case of Chinese urban households. Energy Econ. 34 (6), 1864–1872.
- Guo, J.E., Zhang, Z.K., Meng, L., 2012. China's provincial CO_2 emissions embodied in international and interprovincial trade. Energy Policy 42, 486–497.
- Guo, Y., Tian, J.P., Chertow, M., Chenl. J., 2016. Greenhouse gas mitigation in Chinese ecoindustrial parks by targeting energy infrastructure: a vintage stock model. Environ. Sci. Technol. 50 (20), 11403–11413.
- Hong, J.K., Shen, Q.P., Xue, F., 2016. A multi-regional structural path analysis of the energy supply chain in China's construction industry. Energy Policy 92, 56–68.
- Huang, Y.A., Lenzen, M., Weber, C.L., Murray, J., Matthews, H.S., 2009. The role of inputoutput analysis for the screening of corporate carbon footprints. Econ. Syst. Res. 21 (3), 217–242.
- Hubacek, K., Guan, D.B., Barua, A., 2007. Changing lifestyles and consumption patterns in developing countries: a scenario analysis for China and India. Futures 39 (9),
- Jalas, M., Juntunen, J.K., 2015. Energy intensive lifestyles: time use, the activity patterns of consumers, and related energy demands in Finland. Ecol. Econ. 113, 51–59.
- Jiang, X.M., Zhu, K.F., Green, C., 2015. China's energy saving potential from the perspective of energy efficiency advantages of foreign-invested enterprises. Energy Econ. 49, 104–112
- Kerkhof, A.C., Nonhebel, S., Moll, H.C., 2009. Relating the environmental impact of consumption to household expenditures: an input-output analysis. Ecol. Econ. 68 (4), 1160–1170.
- Lenzen, M., 2003. Environmentally important paths, linkages and key sectors in the Australian economy. Struct. Chang. Econ. Dyn. 14 (1), 1–34.
- Lenzen, M., 2007. Structural path analysis of ecosystem networks. Ecol. Model. 200 (3), 334–342.
- Lenzen, M., Murray, J., 2010. Conceptualising environmental responsibility. Ecol. Econ. 70 (2), 261–270.
- Lenzen, M., Treloar, G., 2002. Differential convergence of life-cycle inventories towards upstream production layers. J. Ind. Ecol. 6 (3–4), 137–160.
- Lenzen, M., Dey, C., Foran, B., 2004. Energy requirements of Sydney households. Ecol. Econ. 49 (3), 375–399.
- Leontief, W., 1970. Environmental repercussions and the economic structure: an inputoutput approach. Rev. Econ. Stat. 52, 262–271.
- Li, M., 2010. Decomposing the change of CO_2 emissions in China: a distance function approach. Ecol. Econ. 70 (1), 77–85.
- Li, J.S., Xia, X.H., Chen, G.Q., Alsaedi, A., Hayat, T., 2016. Optimal embodied energy abatement strategy for Beijing economy: based on a three-scale input-output analysis. Renew. Sust. Energ. Rev. 53, 1602–1610.
- Liu, L.C., Wu, G., 2013. Relating five bounded environmental problems to China's house-hold consumption in 2011–2015. Energy 57, 427–433.
- Liu, H.T., Guo, J.E., Qian, D., Xi, Y.M., 2009. Comprehensive evaluation of household indirect energy consumption and impacts of alternative energy policies in China by input-output analysis. Energy Policy 37 (8), 3194–3204.
- Liu, Z., Geng, Y., Lindner, S., Guan, D.B., 2012a. Uncovering China's greenhouse gas emission from regional and sectoral perspectives. Energy 45 (1), 1059–1068.
- Liu, Z., Geng, Y., Lindner, S., Zhao, H.Y., Fujita, T., Guan, D.B., 2012b. Embodied energy use in China's industrial sectors. Energy Policy 49, 751–758.

- Llop, M., Ponce-Alifonso, X., 2015. Identifying the role of final consumption in structural path analysis: an application to water uses. Ecol. Econ. 109, 203–210.
- Mattila, T., 2012. Any sustainable decoupling in the Finnish economy? A comparison of the pathways and sensitivities of GDP and ecological footprint 2002–2005. Ecol. Indic. 16. 128–134.
- Mattila, T., Koskela, S., Seppälä, J., Mäenpää, I., 2013. Sensitivity analysis of environmentally extended input-output models as a tool for building scenarios of sustainable development. Ecol. Econ. 86 (2), 148–155.
- Meng, F.Y., Zhou, D.Q., Zhou, P., Bai, Y., 2014. Sectoral comparison of electricity-saving potentials in China: an analysis based on provincial input–output tables. Energy 72 (7), 772–782.
- Meng, J., Liu, J.F., Xu, Y., Tao, S., 2015. Tracing primary PM_{2.5} emissions via Chinese supply chains. Environ. Res. Lett. 10 (5), 054005.
- chains. Environ. Res. Lett. 10 (5), 054005.

 Nagashima, F., Kagawa, S., Suh, S., Nansai, K., Moran, D., 2016. Identifying critical supply chain paths and key sectors for mitigating primary carbonaceous PM2.5 mortality in Asia Eron Syst Res. 29 (1) 1–19
- National Bureau of Statistics of the People's Republic of China (NBSC), 2013. China Statistical Yearbook. China Statistics Press, Beijing.
- Ou, J.M., Meng, J., Zheng, J.Y., Mi, Z.F., Bian, Y.H., Yu, X., Liu, J.R., Guan, D.B., 2017. Demanddriven air pollutant emissions for a fast-developing region in China. Appl. Energy 204, 131–142
- Park, H.C., Heo, E., 2007. The direct and indirect household energy requirements in the Republic of Korea from 1980 to 2000-an input-output analysis. Energy Policy 35 (5), 2839–2851.
- Perobelli, F.S., Faria, W.R., Vale, V.D.A., 2015. The increase in Brazilian household income and its impact on CO₂ emissions: evidence for 2003 and 2009 from input-output tables. Energy Econ. 52, 228–239.
- Skelton, A., 2013. EU corporate action as a driver for global emissions abatement: a structural analysis of EU international supply chain carbon dioxide emissions. Glob. Environ. Chang. 23 (6), 1795–1806.
- Skelton, A., Guan, D.B., Peters, G.P., Crawford-Brown, D., 2011. Mapping flows of embodied emissions in the global production system. Environ. Sci. Technol. 45 (24), 10516–10523.
- Statistics Bureau of Guangdong Province (SBG), 1996. Guangdong Statistical Yearbook. China Statistics Press, Beijing.
- Statistics Bureau of Guangdong Province (SBG), 2013. Guangdong Statistical Yearbook. China Statistics Press, Beijing.

- Statistics Bureau of Guangdong Province (SBG), 2016. Guangdong Statistical Yearbook. China Statistics Press, Beijing.
- Tarancon, M.A., Río, P.D., 2012. Assessing energy-related CO₂ emissions with sensitivity analysis and input-output techniques. Energy 37 (1), 161–170.
- Wang, X., Cai, H., Florig, H.K., 2016. Energy-saving implications from supply chain improvement: an exploratory study on China's consumer goods retail system. Energy Policy 95, 411–420.
- Wei, Y.M., Liu, L.C., Fan, Y., Wu, G., 2007. The impact of lifestyle on energy use and CO₂ emission: an empirical analysis of China's residents. Energy Policy 35 (1), 247–257.
- Werfel, S.H., 2017. Household behaviour crowds out support for climate change policy when su-cient progress is perceived. Nat. Clim. Chang. 7 (7), 1–5.
- Wiedenhofer, D., Guan, D.B., Liu, Z., Meng, J., Zhang, N., Wei, Y.M., 2017. Unequal house-hold carbon footprints in China. Nat. Clim. Chang. 7 (1), 75–81.
- Wilting, H.C., 2012. Sensitivity and uncertainty analysis in MRIO modeling; some empirical results with regard to the Dutch carbon footprint. Econ. Syst. Res. 24 (2), 141–171.
- Yan, J.N., Zhao, T., Kang, J.D., 2016. Sensitivity analysis of technology and supply change for CO₂ emission intensity of energy-intensive industries based on input-output model. Appl. Energy 171, 456–467.
- Yang, Z.Y., Dong, W.J., Xiu, J.F., Dai, R.F., Chou, J.M., 2015. Structural path analysis of fossil fuel based CO₂ emissions: a case study for China. PLoS One 10 (9), e0135727.
- Zhang, Y.G., 2013. The responsibility for carbon emissions and carbon efficiency at the sectoral level: evidence from China. Energy Econ. 40 (2), 967–975.
- Zhang, B., Qu, X., Meng, J., Sun, X.D., 2017. Identifying primary energy requirements in structural path analysis: a case study of China 2012. Appl. Energy 191, 425–435.
- Zhao, X.L., Li, N., Ma, C.B., 2012. Residential energy consumption in urban China: a decomposition analysis. Energy Policy 41 (1), 644–653.
- Zhu, Q., Peng, X.Z., Wu, K.Y., 2012. Calculation and decomposition of indirect carbon emissions from residential consumption in China based on the input-output model. Energy Policy 48 (3), 618–626.
- Zhu, B.Z., Wang, K.F., Chevallier, J., Wang, P., Wei, Y.M., 2015. Can China achieve its carbon intensity target by 2020 while sustaining economic growth? Ecol. Econ. 119, 209–216.